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Full Length Research Article

THE DYNAMICS OF SOME CLIMATE VARIABLES ON SOLID WASTE IN NIGERIA USING VECTOR ERROR CORRECTION MODEL

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ABSTRACT
This study investigated the long- run and short-run relationships between solid waste generation in Nigeria and two key climate variables: rainfall and temperature. Employing a Vector Error Correction Model (VECM) analysis on data from 1982 to 2022, then revealed counterintuitive findings. In the long run, lagged rainfall exhibits a negative association with solid waste ($p < 0.05$), potentially explained by increased waste decomposition in wetter conditions. Conversely, lagged temperature showed a positive association ($p < 0.05$), aligning with theories of increased consumption and economic activity in warmer periods. The short-run analysis unveils a self-correcting mechanism in solid waste generation and a statistically significant negative impact of lagged temperature ($p < 0.05$), requiring further investigation. Based on these findings, the study proposed policy implications for waste management strategies and data collection, emphasizing the need for sustainable solutions in the context of climate change.

Keywords: solid waste management; vector error correction model (VECM); cointegration analysis; *Climate Variables.*

INTRODUCTION
Climate change, as elucidated by Abbass et al. (2021), Alhassan (2021), Liu et al. (2022), and Li and Tan (2023), is not just a localized issue but a global phenomenon with profound implications for environmental systems, ecosystems, and human societies. The impacts of climate change on these interconnected elements are multifaceted and can exacerbate existing environmental issues while also creating new challenges. Observations (Olasunkanmi, 2014; Adeniran et al., 2020; Abbass et al., 2021; Alhassan, 2021; Liu et al., 2022; and Li and Tan, 2023) suggest that climate change directly affects environmental systems (weather patterns, precipitation levels, and temperature variations) and ecological processes (pollination, migration patterns, and nutrient cycling), which are vital for the functioning of ecosystems. For example, shifts in temperature and precipitation can affect the timing of flowering and the availability of resources, impacting the reproductive success of plants and the animals that depend on them (Alhassan, 2021; Liu et al., 2022; and Li and Tan, 2023). On a societal level, studies such as those by Hoegh-Guldberg et al. (2018), Cleland et al. (2020), and the IPCC (2022) have noted that the impacts of climate change are far-reaching and severe, affecting weather patterns and leading to crop failures, food shortages, and water scarcity, particularly in vulnerable regions with limited resources and infrastructure.
In Nigeria, solid waste management remains a critical issue due to its significant impact on public health, environmental quality, and sustainable development. According to the World Bank, the country's annual waste generation has increased from approximately 17 million tonnes in 2000 to over 32 million tonnes in 2020. The United Nations Industrial Development Organization (UNIDO, 2022) has observed that Nigeria generates over 32 million tonnes of waste annually, with plastic accounting for 2.5 million tonnes. Urban areas, particularly major cities like Lagos, have emerged as significant contributors to the overall waste generation in Nigeria. Currently, Nigeria generates an average of 0.51 kilograms per capita per day (World Bank, 2022). Along with the quantitative growth in waste generation, the nature of solid waste in Nigeria has also changed, with the share of synthetic waste with complex compounds, especially plastics, glass, and hazardous materials, increasingly larger (Karbassi and Heidari, 2015). The country is among the top 20 nations that contribute 83 percent of the total volume of land-based plastic waste that ends up in the oceans. Unfortunately, there is no national strategy in place to effectively manage and commercialize waste in Nigeria. As a result, more than 200,000 tonnes of plastics from Nigeria end up in the Atlantic Ocean, while over 172.7 million people in the country are living in an unclean environment (Aina and Adeola, 2020).
Evidence has shown that Nigeria experiences diverse climatic conditions due to its geographical location (Adewole et al., 2018; Akhtar et al., 2019; Aiyelaagbe et al., 2019). These conditions, according to Akhtar et al. (2019) and Aiyelaagbe et al. (2019), include rising temperatures, changes in rainfall patterns, high humidity levels, and floods, droughts, among others. Previous research by Guerrero, Maas, and Hogland (2013), Lumbreras and Fernández (2014), Nathanson (2015), Aiyelaagbe et al. (2019), and Otitoloju et al. (2020) have noted that climate change and its associated variables significantly impact solid waste generation and management. For instance, rising temperatures can accelerate organic waste decomposition, potentially increasing methane emissions and requiring adjustments in waste collection frequency (Adewole et al., 2018). Changes in rainfall patterns can influence waste segregation, transportation, and disposal. The increased frequency and intensity of extreme weather events like droughts and floods can disrupt waste collection and processing infrastructure, exacerbating waste management issues (Akhtar et al., 2019).
With a rapidly growing population and changing consumption patterns, which are driving a significant increase in solid waste generation, Nigeria is facing severe environmental and health challenges. However, a critical gap exists in our understanding of how key climate variables like temperature and precipitation directly and indirectly impact the dynamics of solid waste generation across diverse regions and waste types. This lack of knowledge hinders the development of effective and sustainable waste management strategies that adapt to the evolving climate and its multifaceted impacts on waste characteristics, collection efficiency, and disposal outcomes. Consequently, inadequate waste management under a changing climate exacerbates environmental risks like air and water pollution, greenhouse gas

emissions, and vector-borne diseases, disproportionately affecting vulnerable communities and hindering broader sustainability goals. In a previous work, Shehu *et al.* (2024) examined the long run and short run impact of GDP and Real Income on Solid Waste in Nigeria Using Vector Error Correction Model. This present paper aims to address this gap by employing a Vector Error Correction Model (VECM) to analyze the cointegrated relationships and dynamic impacts of temperature and precipitation on solid waste generation in Nigeria.

Nigeria faces a burgeoning solid waste challenge due to rapid population growth and evolving consumption patterns (World Bank, 2023). However, a crucial knowledge gap remains: how key climate variables, like temperature and precipitation, directly and indirectly influence waste generation in Nigeria. Solid waste encompasses household, industrial, commercial, and agricultural discards (Osinowo et al*.,* 2020). Temperature, precipitation, and extreme weather events are key climate variables influencing its generation (UNEP, 2021). Higher temperatures accelerate organic waste decomposition, potentially increasing methane emissions, a potent greenhouse gas (IPCC, 2022). Intense rainfall events can overwhelm waste management infrastructure, leading to leachate contamination and waste dispersion (UNEP, 2021). Changes in rainfall patterns can affect waste management practices, such as disrupting waste collection and disposal (UNFCCC, 2022). More frequent and intense storms can damage waste infrastructure, leading to waste spills and contamination (World Bank, 2023).

The Atmospheric Heat Trapping (Greenhouse Effect), proposed by Joseph Fourier in 1824 and further developed by scientists like Eunice Newton Foote and Svante Arrhenius, explains how specific atmospheric gases trap heat, contributing to global warming (NASA, 2023). The basic premise of atmospheric heat trapping is that certain gases in the atmosphere, known as greenhouse gases (GHGs), absorb some of the long-wave infrared radiation emitted by Earth's surface and atmosphere. This trapped energy contributes to warming the planet, similar to how a greenhouse traps heat from sunlight. This theory helps us analyze the dynamics of climate variables on solid waste. In a warming climate, landfills could experience accelerated organic decomposition, potentially impacting methane emissions and landfill stability (IPCC, 2022).

A growing body of evidence suggests climate change significantly impacts on a number of factors (World Bank, 2023). The first of such studies is the work of Li and Tan (2023) who explored strategies to enhance pollution oversight by local governments while minimizing collusion with incineration plants. The authors proposed a differential game model simulating interactions between these entities. Their findings revealed that higher environmental assessment standards incentivize stricter oversight by local governments.

In another related study, Ani, et al. (2022) investigated the changing impact of climate change on food and human security in Nigeria. It employed quantitative and qualitative data from various sources, including Statistical data on climate variability, Semi-structured interviews, Reports from international NGOs, and Focus group discussions with farmers, government officials, and other stakeholders. The study found that climate change negatively affects food security and contributes to armed conflicts over natural resources, jeopardizing human security.

Michalak and Szyja (2023) use a "benchmarking" approach to compare Poland's climate change adaptation policy with other EU countries. Analyzing 12 projected indicators of economic and climate impact, the study reveals contrasting trends: while Poland has the lowest projected impact among Western EU nations, its adaptation policies are the weakest. This disparity is reversed when comparing Poland to other 2004 EU entrants. Notably, the study highlights a broader European concern - despite rising negative climate consequences, adaptation policy implementation remains insufficient overall.

Kara et al. (2021**)** investigated the impact of climate change risk on supply chain performance. The Methodology involved Three-phase mixed approach: Cognitive mapping: Capturing expert-based relationships between climate risks and performance; Survey: Identifying key climate factors and their influence on specific performance dimensions; and System dynamics modeling: Assessing the systemic impact of climate change on various performance metrics. The study found that Climate change significantly reduces natural resource availability and capacity, leading to Stock-outs, increased inventory costs, Bottlenecks in procurement, manufacturing, and logistics, and Supply chain efficiency and effectiveness decrease with increasing climate risks. The study concluded that Climate change poses a significant threat to supply chain performance, necessitating proactive risk management strategies.

Alejandra et al. (2023) examined the impact of climate change on international trade flows compared to domestic flows. Gravity model with 67 countries from 1986 to 2016, using temperature and extreme weather events as climate change indicators. The study found that International trade generally less affected by temperature changes than domestic flows. Other findings by the study include Extreme weather events negatively impact international trade, primarily biological events, temperature extremes, storms, and landslides; China and Japan strongly influence overall results, particularly for storms (China) and extreme temperatures (Japan); and General Equilibrium analysis suggests insect infestation and extreme temperatures have the most detrimental impact on welfare. It was concluded that Climate change, especially extreme weather events, poses a significant risk to international trade, emphasizing the need for adaptation and mitigation strategies.

Mavodyo (2023) investigated the impact of climate change on various food insecurity indicators in the Southern African Development Community (SADC) region. The study adopted a System Generalized Method of Moments (GMM) estimator, analyzing multiple indicators including crop yield, food affordability, malnutrition, and a general food insecurity measure. It was found that: Precipitation significantly impacts all four indicators, both linearly and non-linearly; the greatest impact is on food affordability, followed by malnutrition; Temperature, alone, has no significant effect but gains significance when interacting with precipitation; and increased precipitation and climate change mitigation are crucial policy priorities. The study concluded that Climate change, particularly precipitation changes, significantly affects various aspects of food insecurity in the SADC region. The study emphasizes the need for sustainable irrigation programs, comprehensive climate change mitigation strategies, and actions to ensure food affordability and access to nutritious meals, especially for vulnerable populations.

In another study, Murat et al. (2022) analyzed the effect of climate change on aggregate output in middle- and high-income countries. The study employed a Dynamic panel data analysis for 1990-2016, incorporating temperature and precipitation as climate indicators within a Cobb-Douglas production function. Generalized Method of Moments (GMM) estimation and Granger causality tests were used. The study found that Middle-income countries experienced both temperature and precipitation have negative and statistically significant impacts on aggregate output. While High-income countries temperature has a positive but negligible effect on aggregate output, while precipitation has no significant effect. The study concluded that climate change negatively impacts aggregate output in middle-income countries, while high-income countries experience minimal positive or no effects from temperature changes. This highlights the varying vulnerability of different economic groups to climate change.

Mavodyo (2023) investigated the impact of climate change on various food insecurity indicators in the Southern African Development Community (SADC) region. The methodology includes System Generalized Method of Moments (GMM) estimator, analyzing multiple indicators including crop yield, food affordability, malnutrition, and a general food insecurity measure. The study found that precipitation significantly impacts all four indicators, both linearly and non-linearly. Other findings include: the greatest impact is on food affordability, followed by malnutrition. Temperature, alone, has no significant effect but gains significance when interacting with precipitation, and increased precipitation and climate change mitigation are crucial policy priorities. The study concluded that Climate change, particularly precipitation changes, significantly affects various aspects of food insecurity in the SADC region. The study emphasizes the need for sustainable irrigation programmes, comprehensive climate change mitigation strategies, and actions to ensure food affordability and access to nutritious meals, especially for vulnerable populations.

Jain, et al. (2023) quantified the environmental cost of food waste in the United States and propose policy solutions. More specifically, the study analyzed greenhouse gas (GHG) emissions from food waste in the US between 1997 and 2017, comparing animal-based vs. plant-based products. Proposes a mix of economic incentives, regulations, and public awareness campaigns to address food waste. The study found that Food waste significantly increases greenhouse gas emissions, costing the US billions of dollars annually; Animal-based products contribute considerably more to GHG emissions per capita compared to plant-based products; and Between 1997 and 2017, food waste-related GHG emissions in the US increased by 10 billion kgCO2eq and costs by 6 billion USD.

Ho-Jyun and Hongtu (2023) examined the impact of a greenhouse gas emissions trading scheme (GHG-ETS) on industrial effluent discharge in the Pearl River Delta, China. The study employed Difference-in-Differences (DID) analysis comparing regions with and without GHG-ETS implementation from 2008 to 2019. The study found that the Implementation of GHG-ETS leads to higher actual energy costs for manufacturers, even with sufficient carbon emission quotas. Other findings include GHG-ETS incentivizes industries to increase sewage discharge to marginally reduce energy consumption. Compared to non-GHG-ETS regions, Pearl River Delta industries saw a significant increase in sewage discharge per unit of industrial value added after the scheme's implementation. The study suggests that GHG-ETS, while aiming to reduce greenhouse gas emissions, may have unintended consequences like increased industrial effluent discharge, highlighting the need for comprehensive environmental policy design.

Carrilho-Nunes and Catalão-Lopes (2022) analyzed the impact of environmental policy and technology transfer on greenhouse gas (GHG) emissions in Portugal. The study employed a statistical model to examine the influence of policy instruments (feed-in tariffs, fossil fuel support), technology transfer, and other factors on GHG emissions. A Positive impact of environmental policy with Stringent environmental policies effectively reduce GHG emissions in Portugal was found. The study also noted a Potential drawback of technology transfer as technology transfer, while aiming to improve sustainability, might initially increase GHG emissions ("Green Paradox"). It was concluded that study highlights the effectiveness of environmental policy in curbing emissions while urging caution with technology transfer due to its potential unintended consequences. It suggests policymakers carefully consider these dynamics for a smooth transition to a sustainable economy.

Rising temperatures threaten the interior continent with water scarcity, glacier melt, and potential extinction of plant species (Gampe *et al*., 2016; Dimri *et al*., 2018; Mannig *et al*., 2018; Shaffril et al., 2018; Goes et al., 2020; Schuurmans, 2021; Mihiretu et al., 2021). Coastal ecosystems face devastation from rising temperatures, insect outbreaks, health problems, and seasonal changes (Perera et al., 2018; Phillips, 2018; Hussain et al., 2018; Abbasi et al., 2021c). Globally, insufficient infrastructure and adaptive capacity exacerbate these issues (IPCC, 2013). Other significant concerns include lack of environmental education, outdated consumer behavior, and inadequate legislation (Hussain et al., 2018; Abassi et al., 2021c). By 2050, projected 2-3°C temperature rise and rainfall pattern shifts could have serious consequences (Gorst et al., 2018; Huang et al., 2022). Natural and environmental disasters lead to losses in agriculture, system rehabilitation, and technology rebuilding (Ali & Erenstein, 2017; Ramankutty et al., 2018; Yu et al., 2021). Additionally, recent years have seen smog-related health issues and road accidents due to poor visibility.

Global agriculture, a major contributor to greenhouse gas emissions (30-40%), is also significantly impacted by climate change (Thornton & Lipper, 2014; Grieg; Mishra et al., 2021; Ortiz et al., 2021). Agro-environmental and climatic factors influencing agricultural productivity, such as floods, droughts, and forest fires, are heavily impacted by changing precipitation patterns (Huang, 2004). Reliance on exhaustible resources further fuels agriculture's vulnerability (Godfray et al., 2010). Declining agricultural productivity negatively impacts farmers' livelihoods and contributes to poverty, as food and water security are compromised by climate change (Rosenzweig et al., 2014; Ortiz et al., 2021). As a crucial part of economies, particularly in developing countries, agricultural systems influence overall well-being and household income (Schlenker & Roberts, 2009). Rising greenhouse gas concentrations (CH_4, CO_2, N_2O) have reached unprecedented levels in recent centuries (Stocker et al., 2013; Usman & Makhdum, 2021). Climate change, driven by both natural and human factors (Karami, 2012), is projected to cause global temperature increases of 1-3.7°C by the end of the century (Pachauri et al., 2014). These rising temperatures pose severe threats to crop growth and global food security (Reidsma et al., 2009).

Literature documenting CC-driven species extinction is extensive (Urban, 2015; Beesley et al., 2019). Predictions for the 21st century are grim, with numerous species facing potential demise (Pereira et al., 2013; Abbass et al., 2019). While northward shifts may offer some relief for mountain-dwelling species seeking optimal climates, habitat fragmentation and limited range can leave them trapped in unsuitable environments (Dullinger et al., 2012). The American pika's extirpation in some regions exemplifies this (Stewart et al., 2015). Analyzing long-term ecological data is crucial

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for rigorously identifying pre- and post-CC patterns at species and ecosystem levels (Manes et al., 2021; Testa et al., 2018). Unfortunately, such data is often scarce, necessitating continued focus on acquiring and utilizing it effectively.

Forests play a crucial role in regulating global climate and nutrient cycles (FAO, 2018; Reichstein & Carvalhais, 2019; Rehman et al., 2021). However, disturbances like climate change significantly impact their structure, function, and health (Zhang et al., 2017; EPA, 2018). Rising temperatures and altered precipitation patterns tend to disrupt forest growth, productivity, and species composition (Allen et al., 2010; Flannigan et al., 2013; Millar & Stephenson, 2015; Hubbart et al., 2016; Rehman et al., 2021). Increased droughts and storms on the other hand, exacerbate stress, weaken trees, and damage forests (Diffenbaugh et al., 2017; Lehner et al., 2017; Hartmann et al., 2018; Martínez-Alvarado et al., 2018; Brázdil et al., 2018). These devastate forests and alter ecosystems (EPA, 2018).

Forests sustain the livelihoods of around 1.6 billion people globally, with many relying heavily on them (Bank, 2008; Sunderlin et al., 2005; Wasiq & Ahmad, 2004). Climate change poses unique challenges for these communities. Climate disruptions affect agricultural practices, leading to decreased crop yields and income (Macchi et al., 2008; Cruz, 2015). Changes in rainfall patterns and pest outbreaks threaten food security for forest-dependent communities. Increased temperatures and altered precipitation patterns lead to the spread of waterborne and vector-borne diseases (Xu et al., 2008; Gunter et al., 2008; Cell, 2009; Fardous & Sharma, 2012).

From the above, it should be noted that existing literature predominantly focuses on the influence of climate factors on the ecosystem, environment among others, with investigations into solid waste management receiving comparatively less attention. This study is undertaken to explore the dynamic relationship between some climate factors and solid waste.

MATERIALS AND METHODS

This study analyzes the impact of climate variables (rainfall and temperature) on solid waste generation in Nigeria. Data was collected from secondary sources including the National Bureau of Statistics' Annual Abstract and the World Bank Development Indicators. The data cover a period of 41 years, from 1982 to 2022, to capture longitudinal trends and analyze their potential influences on solid waste generation.

The study variables include Solid Waste Generation (SW) measured in tons, representing the total amount of waste generated within a specific year; rainfall measured in millimeters of precipitation annually across the selected regions in Nigeria; and temperature which is measured in degrees Celsius. The dynamics among these variables are analyzed using a Vector Error Correction Model (VECM), which extends the framework of a vector autoregressive (VAR) model by integrating an error correction term into each equation (Adenomon, et al., 2017). The inclusion of the error correction term in each equation of the VAR accounts for the disequilibrium between variables in the short run, allowing for the analysis of the adjustments that occur in response to any deviations from the long-run equilibrium. By considering the speed and direction of these adjustments, the VECM provides insights into the interdependencies and feedback mechanisms among the variables under investigation though ARDL model could be an alternative to VECM (Adenomon and Ojo, 2020). In summary, the utilization of a Vector Error Correction Model (VECM) enhances the analysis by capturing the short-run dynamics and the speed of adjustment towards long-run equilibrium, thereby providing a comprehensive understanding of the interrelationships among the variables in the system.

Theoretically, the VAR model is specified thus:

Let $\Upsilon_t = (y_{1t}, y_{2t}, \ldots, y_{nt})^0$ denote an (n - 1) vector of time series variables.

The basic p-lag *vector autoregressive* (VAR(p)) model has the form

$$Y_t = c + \pi_1 Y_{1-t} + \pi_2 Y_{t-2}` + \cdots + \pi_p Y_{t-p} + £_t, \quad t = 1, \ldots, T \qquad (1)$$

Where π_i are (n x n) coefficient matrix and $£_t$ is an (n × 1) unobservable zero mean white noise vector process (serially uncorrelated or independent) with time invariant covariance matrix Σ. A bivariate VAR (2) model equation by equation has the form:

$$\begin{pmatrix} y_{1t} \\ y_{2t} \end{pmatrix} = \begin{pmatrix} c_1 \\ c_2 \end{pmatrix} + \begin{pmatrix} \pi_{11}^1 & \pi_{12}^1 \\ \pi_{21}^1 & \pi_{22}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \end{pmatrix} + \begin{pmatrix} \pi_{11}^2 & \pi_{12}^2 \\ \pi_{21}^2 & \pi_{22}^2 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \end{pmatrix} + \begin{pmatrix} £_{1t} \\ £_{2t} \end{pmatrix} \qquad (2)$$

where cov ($£_{1t}, £_{2t}$) = σ_{12} for t = s; 0 otherwise.

From the above, it can be observed that each equation has the same regressors — lagged values of y_{1t} and y_{2t}. Hence, the VAR(p) model is just a seemingly unrelated regression (SUR) model with lagged variables and deterministic terms as common regressors.

In lag operator notation, the VAR(p) is written as

$$\pi(L)Y_t = c + \varepsilon_t$$

where $\pi(L) = I_\pi - \pi_1 L - \ldots - \pi_p L_p$.

The VAR(p) is stable if the roots of det $(I_\pi - \pi_{1z} - \cdots - \pi p_z^p) = 0$ (3)

The mean-adjusted form of the VAR(p) is then

$$Y_t - \mu = \Pi_1(Y_{t-1-\mu}) + \Pi_2(Y_{t-2-\mu}) + \cdots + \Pi_p(Y_{t-p-\mu}) + \varepsilon_t \qquad (4)$$

Using the variables for this study, an appropriate VECM model can be formulated as follows

$$\Delta yt = \alpha\beta' yt - 1 + \sum_{i=1}^{p-1} \Gamma_i \Delta y_{t-1} + \varepsilon t \qquad (5)$$

where:

Δ: Operator differencing,

$\Delta y_t = y_t - y_{t-1}\, y_{t-i}$: Vector variable endogenous with the 1st lag

ε_t: Vector residual.

Γi: Matrix with order k × k of coefficient Endogenous of the i-th variable

α: Vector adjustment, matrix with order (k × r)

β: Vector cointegration (long-run parameter) matrix (k × r)

The VECM in this study comprises three core variables and is presented as equation 3.6 below

$$\Delta(SW) = \Upsilon_0 + \Upsilon_1 SW\phi_{t-1} + \sum_{i=1}^{q3} a_{3i}\,\Delta(\mathrm{SW}_{t-i}) + \sum_{i=1}^{r3} \psi_{3i}\,\Delta(Rainfall_{t-i}) + \sum_{i=1}^{k3} \eta_{3i}\,\Delta(\mathrm{Temperature}_{t-i}) + \varepsilon_{3t} \qquad (6)$$

Where Υ_0 is the intercept term, representing the constant or baseline level of Solid Waste Generation when all other variables are zero and $\Upsilon_1 SW\phi_{t-1}$ is the Error correction coefficient, quantifying the speed of adjustment towards equilibrium. Both parameters would be estimated using a seemingly unrelated regressions (SUR) estimation technique. Rainfall and Temperature are as previously defined. Δ is operator differencing, and ε_t represents Vector residual.

Other econometrics tests employed include the **Augmented Dickey-Fuller (ADF) Test specified as:**
$\Delta Y_t = \alpha + \beta_t + \gamma Y_{t-1} + \delta_1 \Delta Y_{t-1} + \ldots + \delta_{p-1} \Delta Y_{t-p+1} + \varepsilon_t$
Where:

- Y_t: The time series variable being tested for a unit root (LNSW, LNRainfall, and LNTemperature).
- ΔY_t: The first difference of Y_t (Y_t - Y_{t-1}).
- α: The intercept term.
- β: The coefficient on the time trend (t).
- γ: The coefficient on the lagged value of Y (Y_{t-1}). This is the key parameter for testing the unit root hypothesis.
- δ_1, ..., δ_{p-1}: Coefficients on lagged differences of Y_t, used to control for serial correlation.
- ε_t: The error term.

The null hypothesis that Y_t has a unit root (non-stationary) will be tested.
The study also employed the **Johansen Cointegration Test:**
$Y_t = \Pi Y_{t-1} + \Gamma X_t + \varepsilon_t$
Where Y_t: A vector of time series variables, including LNSW, LNRainfall, and LNTemperature.

i. Π: A matrix of coefficients capturing long-run relationships between variables in Yt.
ii. Γ: A matrix of coefficients capturing short-run dynamics between variables in Yt.
iii. Xt: A vector of exogenous variables (not included in the model).

RESULTS AND DISCUSSION
In this section, we present the empirical findings derived from the Vector Error Correction Model (VECM) analysis conducted in this study. Prior to the estimation of the VECM, we performed descriptive analysis, Unit Root tests, and Johansen Cointegration tests to assess the data background, stationarity, and cointegration of the series. The dataset includes 41 observations.

Data Background and Diagnostics Tests
Descriptive analysis of the data as presented in Table 4.1 shows that Solid waste generation in Nigeria between 1982 and 2022 is high with an average of 20.5 billion tons annually. Rainfall averages 209.6 mm, and temperature averages 27.26°C. Median values align closely with means, suggesting minimal skewness in distributions. However, large standard deviations for SW and RAIN (12.9 billion tons and 5.6 mm) indicate substantial variations in these variables. The smaller standard deviation for TEMP (0.32°C) suggests less year-to-year fluctuation. Positive skewness for RAIN (1.91) indicates more years with lower rainfall compared to higher values. Negative skewness for TEMP (-0.44) implies slightly more years with warm temperatures. Kurtosis values exceeding 3 (RAIN: 7.58, TEMP: 3.14) suggest heavier tails than a normal distribution, implying potential outliers or non-normality. Probabilities of Jarque-Bera test exceeding 0.05 for SW and TEMP (0.29 and 0.51, respectively) suggest their distributions cannot be rejected as normal at a 5% significance level. However, RAIN's probability (0.00) confirms a non-normal distribution.
Concerning diagnostic tests, the ADF statistics show that all the three series became stationary after the first difference. The Cointegration tests using Johansen confirm strong evidence of 3 cointegrating equations using Trace test indicates and Max-eigenvalue test, establishing a foundation for the subsequent VECM analysis.

Estimated VECM Equations
Long-Run Dynamics between Climate Variables and Solid Waste in Nigeria
The Estimated VECM models illustrate the long-run effects of Climate Variables on Solid Waste in Nigeria

$$\mathrm{LNSW}(-1) = -\ 104.8807 - 1.403156\ \mathrm{LNRAIN}(-1) + 41.07405\ \mathrm{LNTEMP}(-1)$$

The above equation describes the long-run equilibrium relationship between the log of solid waste (LNSW), log of rainfall (LNRAIN), and log of temperature (LNTEMP). The model reveals a statistically significant ($p < 0.05$) negative association between lagged rainfall and solid waste. Conversely, lagged temperature exhibits a positive and significant ($p < 0.05$) relationship with solid waste over the long term. The negative impact of rainfall on long-run solid waste generation merits further investigation, as it appears counterintuitive. A potential explanation lies in increased waste decomposition driven by higher rainfall. This aligns with the decomposition theory, which posits that environmental factors like moisture and temperature significantly influence waste degradation rates. Observations have also supported this notion, indicating that wetter conditions accelerate the breakdown of organic matter, leading to reduced waste accumulation over time.
On the other hand, the positive association between temperature and solid waste is more intuitive. Several theoretical frameworks, including the consumption theory and the economic activity theory, support this finding. The consumption theory suggests that higher temperatures lead to increased consumption of packaged goods, consequently generating more waste. Similarly, the economic activity theory posits that warmer temperatures often coincide with increased construction and industrial activity, both of which contribute to higher waste generation.

Short-Run Dynamics between Climate Variables and Solid Waste in Nigeria
Building upon the long-run analysis, the study estimates short-run effects and Error Correction Mechanisms (ECM).

$$\mathrm{D(LNSW)} = 0.169703 - 0.196814\ \mathrm{D}\big(\mathrm{LNSW}(-1)\big) - 0.311720\ \mathrm{D}\big(\mathrm{LNRAIN}(-1)\big) - -4.944817\ \mathrm{D}\big(\mathrm{LNTEMP}(-1)\big) - 0.284093 ECM(-1)$$

The short-run VECM analysis reveals that the solid waste generation model converges towards its long-run equilibrium at a rate of 28.41% per period ($p < 0.05$). This indicates a relatively swift self-adjustment mechanism within the system. Interestingly, even without changes in rainfall or temperature, the model exhibits a baseline tendency for solid waste to increase in the short run (constant term = 0.169703).
The negative coefficient associated with the lagged change in solid waste (-0.196814, $p < 0.5$) suggests a self-correcting mechanism. Essentially, larger past increases in solid waste lead to smaller current increases, signifying an inherent stabilizing force within the system.
While the lagged change in rainfall exhibits a negative coefficient (-

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0.311720), its statistical insignificance ($p > 0.5$) casts doubt on its practical impact. Although this finding aligns with the proposed decomposition explanation, further investigation is warranted due to the lack of robust evidence.

The most intriguing finding lies in the negative and statistically significant coefficient associated with the lagged change in temperature (-4.944817, $p < 0.5$). This implies that past increases in temperature lead to larger decreases in current solid waste generation compared to rainfall. This counterintuitive result necessitates further exploration to understand the underlying mechanisms at play.

Conclusion and Policy Implication

This study employed a Vector Error Correction Model (VECM) to analyze the dynamic relationship between solid waste generation in Nigeria and two key climate variables: rainfall and temperature. Following the analysis of data, the study concludes that Lagged rainfall is negatively associated with solid waste ($p < 0.05$) in the long run, potentially due to increased waste decomposition in wetter conditions, and that Lagged temperature is positively associated with solid waste ($p < 0.05$) in the long run, consistent with theories like increased consumption and economic activity in warmer periods.

In the terms of short run, the study found that solid waste model converges towards long-run equilibrium at a rate of 28.41% per period ($p < 0.05$), and the Lagged changes in solid waste exhibit a self-correcting mechanism. Another short run finding is that the negative and statistically significant coefficient of lagged temperature (-4.944817, $p < 0.5$) requires further investigation due to its counterintuitive nature.

Based on these findings, several policy implications emerge:

1. **Waste Management Strategies:**
   i. **Rainfall:** Explore and implement technologies that accelerate organic waste decomposition to capitalize on the observed positive impact of rainfall.
   ii. **Temperature:** Encourage sustainable consumption practices and promote waste reduction initiatives in sectors likely to increase their activity during warmer periods (e.g., construction, tourism).
   iii. Investigate the specific waste composition (e.g., organic vs. inorganic) and its relationship to climate variables.
   iv. Develop and implement effective policy interventions to promote sustainable waste management practices in the context of climate change.
2. **Data Collection and Research:**
   i. Conduct further research to elucidate the mechanisms behind the counterintuitive negative association between temperature and solid waste.
   ii. Explore potential non-linearities and alternative model specifications to gain a more nuanced understanding of the system.

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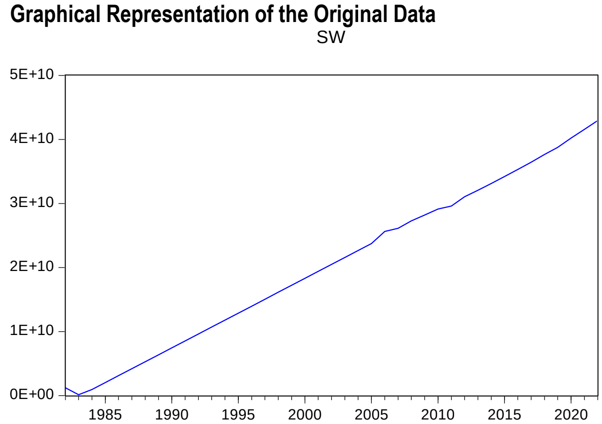
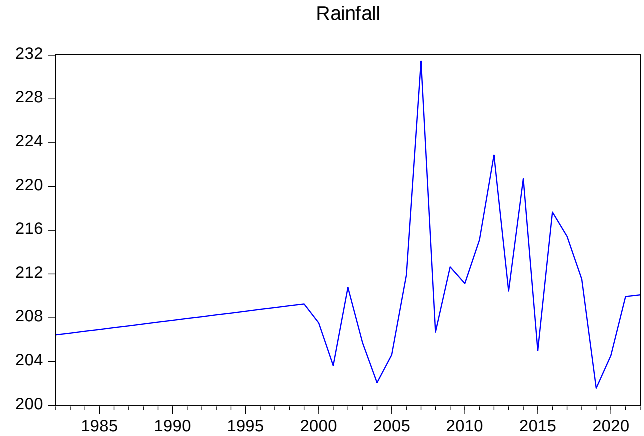
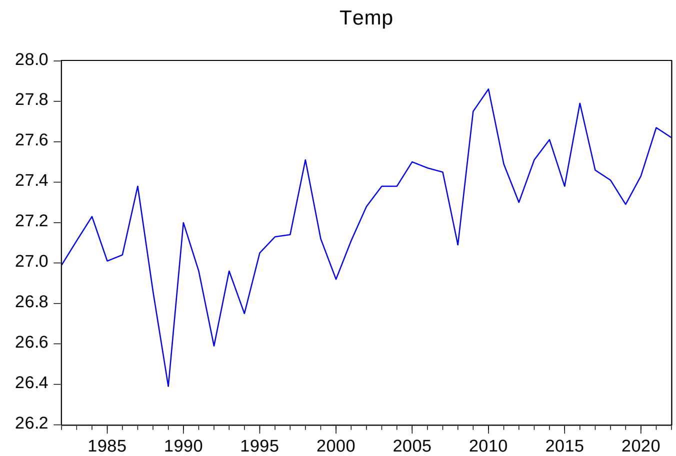
Appendix I
The dynamics of climate variables on Solid Waste in Nigeria using Vector Error Correction Model
Descriptive statistics of Original Data

	SW	RAIN	TEMP
Mean	2.05E+10	209.6185	27.25780
Median	2.05E+10	208.2657	27.29000
Maximum	4.29E+10	231.4564	27.86000
Minimum	1.31E+08	201.5763	26.39000
Std. Dev.	1.29E+10	5.599373	0.318092
Skewness	0.031876	1.910313	-0.439379
Kurtosis	1.798150	7.582060	3.142737
Jarque-Bera	2.474534	60.80379	1.354004
Probability	0.290176	0.000000	0.508138
Sum	8.42E+11	8594.358	1117.570
Sum Sq. Dev.	6.64E+21	1254.119	4.047302
Observations	41	41	41

Graphical Representation of the Original Data





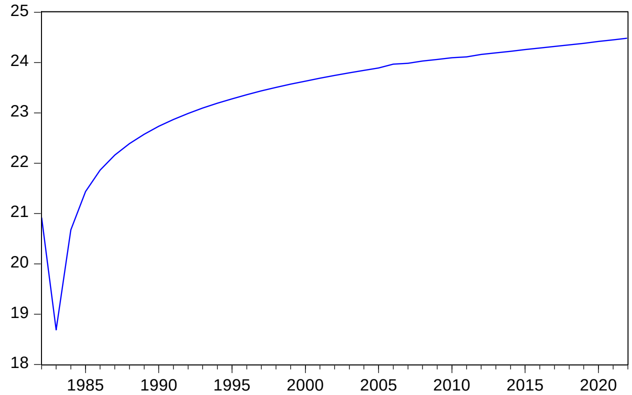


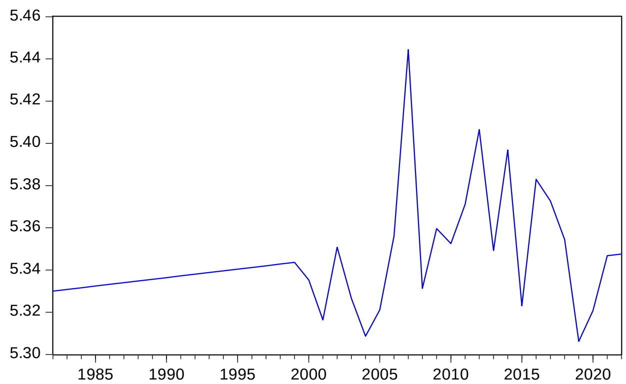
Descriptive statistics of transformed Data

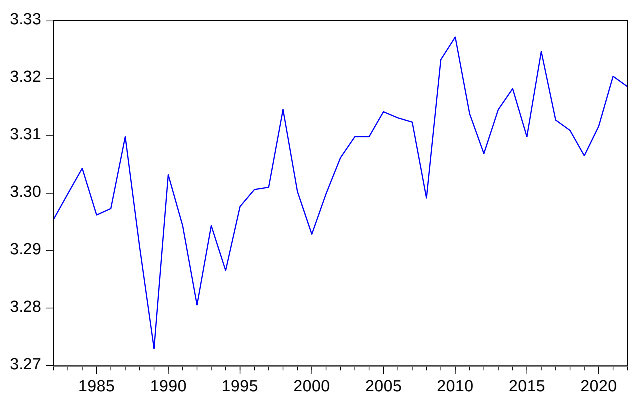
	LNSW	LNTEMP	LNRAIN
Mean	23.34339	3.305273	5.344952
Median	23.74225	3.306520	5.338814
Maximum	24.48321	3.327192	5.444391
Minimum	18.68830	3.272985	5.306168
Std. Dev.	1.214078	0.011701	0.026089
Skewness	-1.902734	-0.473394	1.798238
Kurtosis	6.942576	3.195224	7.111016
Jarque-Bera	51.29354	1.596472	50.96828
Probability	0.000000	0.450122	0.000000
Sum	957.0790	135.5162	219.1430
Sum Sq. Dev.	58.95943	0.005477	0.027226
Observations	41	41	41

Graphical Representation of the Transformed Data

 https://dx.doi.org/10.4314/swj.v19i1.11







Unit Root Test for Stationarity for Solid Waste

Null Hypothesis: LNSW has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-2.800185	0.0682
Test critical values:	1% level	-3.626784	
	5% level	-2.945842	
	10% level	-2.611531	

*MacKinnon (1996) one-sided p-values.

Unit Root Test for Stationarity for Solid Waste at First Difference

Null Hypothesis: D(LNSW) has a unit root
Exogenous: Constant
Lag Length: 3 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.612798	0.0007
Test critical values:	1% level	-3.626784	
	5% level	-2.945842	
	10% level	-2.611531	

*MacKinnon (1996) one-sided p-values.

Unit Root Test for Stationarity for Rain

Null Hypothesis: LNRAIN has a unit root
Exogenous: Constant
Lag Length: 0 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.238031	0.0001
Test critical values:	1% level	-3.605593	
	5% level	-2.936942	
	10% level	-2.606857	

*MacKinnon (1996) one-sided p-values.

Unit Root Test for Stationarity for Rain at First Difference

Null Hypothesis: D(LNRAIN) has a unit root
Exogenous: Constant
Lag Length: 4 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.057407	0.0393
Test critical values:	1% level	-3.632900	
	5% level	-2.948404	
	10% level	-2.612874	

*MacKinnon (1996) one-sided p-values.

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Unit Root Test for Stationarity for Temperature

Null Hypothesis: LNTEMP has a unit root

Exogenous: Constant

Lag Length: 2 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-1.122868	0.6968
Test critical values:	1% level	-3.615588	
	5% level	-2.941145	
	10% level	-2.609066	

*MacKinnon (1996) one-sided p-values.

Unit Root Test for Stationarity for Temperature at First Difference

Null Hypothesis: D(LNTEMP) has a unit root

Exogenous: Constant

Lag Length: 9 (Automatic - based on AIC, maxlag=9)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-3.268267	0.0257
Test critical values:	1% level	-3.670170	
	5% level	-2.963972	
	10% level	-2.621007	

*MacKinnon (1996) one-sided p-values.

Johansen Cointegration test For Solid Waste, Rainfall and Temperature

Date: 01/08/24 Time: 22:23
Sample (adjusted): 1984 2022
Included observations: 39 after adjustments
Trend assumption: Linear deterministic trend
Series: LNSW LNRAIN LNTEMP
Lags interval (in first differences): 1 to 1

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.939975	132.6586	29.79707	0.0000
At most 1 *	0.333324	22.95180	15.49471	0.0031
At most 2 *	0.167279	7.139194	3.841466	0.0075

Trace test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.939975	109.7068	21.13162	0.0001
At most 1 *	0.333324	15.81261	14.26460	0.0282
At most 2 *	0.167279	7.139194	3.841466	0.0075

Max-eigenvalue test indicates 3 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Lag Order Selection Criteria for the Endogenous Variables

VAR Lag Order Selection Criteria

Endogenous variables: LNSW LNRAIN LNTEMP

Exogenous variables: C

Date: 01/08/24 Time: 22:26

Sample: 1982 2022

Included observations: 37

Lag	LogL	LR	FPE	AIC	SC	HQ
0	168.0367	NA	2.68e-08	-8.920905	-8.790290	-8.874857
1	290.5909	218.6102	5.80e-11	-15.05897	-14.53651	-14.87478
2	330.9310	65.41627*	1.08e-11*	-16.75302*	-15.83872*	-16.43069*
3	336.7192	8.447718	1.32e-11	-16.57942	-15.27327	-16.11894
4	347.1569	13.54082	1.29e-11	-16.65713	-14.95914	-16.05851

* indicates lag order selected by the criterion

LR: sequential modified LR test statistic (each test at 5% level)

FPE: Final prediction error

AIC: Akaike information criterion

SC: Schwarz information criterion

HQ: Hannan-Quinn information criterion

Estimated Result of VECM Showing Long Run and Short Run Impact of Rainfall and Temperature on Solid Waste

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Date: 01/08/24 Time: 22:28
Sample (adjusted): 1984 2022
Included observations: 39 after adjustments
Standard errors in ( ) & t-statistics in [ ]

Cointegrating Eq:	CointEq1		
LNSW(-1)	1.000000		
LNRAIN(-1)	1.403156 (2.40657) [0.58305]		
LNTEMP(-1)	-41.07405 (4.73812) [-8.66884]		
C	104.8807		
Error Correction:	**D(LNSW)**	**D(LNRAIN)**	**D(LNTEMP)**
CointEq1	-0.284093 (0.01512) [-18.7924]	-0.001741 (0.00501) [-0.34732]	0.001875 (0.00161) [1.16740]
D(LNSW(-1))	-0.196814 (0.03048) [-6.45759]	0.001313 (0.01011) [0.12997]	-0.003360 (0.00324) [-1.03779]
D(LNRAIN(-1))	-0.311720 (0.45507) [-0.68500]	-0.538044 (0.15090) [-3.56567]	-0.116441 (0.04834) [-2.40903]
D(LNTEMP(-1))	-4.944817 (1.44612) [-3.41937]	0.311533 (0.47952) [0.64968]	-0.201899 (0.15360) [-1.31443]
C	0.169703 (0.01529) [11.0992]	0.000345 (0.00507) [0.06796]	0.000961 (0.00162) [0.59184]
R-squared	0.928377	0.273270	0.279183
Adj. R-squared	0.919951	0.187773	0.194380
Sum sq. resids	0.298777	0.032851	0.003371
S.E. equation	0.093742	0.031084	0.009957
F-statistic	110.1773	3.196233	3.292167
Log likelihood	39.65800	82.70843	127.1069
Akaike AIC	-1.777333	-3.985048	-6.261892
Schwarz SC	-1.564056	-3.771771	-6.048615
Mean dependent	0.148587	0.000430	0.000478
S.D. dependent	0.331326	0.034490	0.011093

Determinant resid covariance (dof adj.)	5.96E-10
Determinant resid covariance	3.95E-10
Log likelihood	256.2033
Akaike information criterion	-12.21555
Schwarz criterion	-11.44776
Number of coefficients	18

VEC Residual Serial Correlation LM Tests
Date: 01/08/24 Time: 22:31
Sample: 1982 2022
Included observations: 39

Null hypothesis: No serial correlation at lag h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	77.96052	9	0.0000	14.60494	(9, 70.7)	0.0000

Null hypothesis: No serial correlation at lags 1 to h

Lag	LRE* stat	df	Prob.	Rao F-stat	df	Prob.
1	77.96052	9	0.0000	14.60494	(9, 70.7)	0.0000

*Edgeworth expansion corrected likelihood ratio statistic.

VEC Residual Normality Tests
Orthogonalization: Cholesky (Lutkepohl)
Null Hypothesis: Residuals are multivariate normal
Date: 01/08/24 Time: 22:32
Sample: 1982 2022
Included observations: 39

Component	Skewness	Chi-sq	df	Prob.*
1	-0.167484	0.182330	1	0.6694
2	0.863238	4.843674	1	0.0277
3	0.898298	5.245110	1	0.0220
Joint		10.27111	3	0.0164

Component	Kurtosis	Chi-sq	df	Prob.
1	3.721236	0.845295	1	0.3579

2	6.243088	17.09113	1	0.0000
3	3.825231	1.106634	1	0.2928
Joint		19.04306	3	0.0003

Component	Jarque-Bera	df	Prob.
1	1.027625	2	0.5982
2	21.93481	2	0.0000
3	6.351744	2	0.0418
Joint	29.31417	6	0.0001

*Approximate p-values do not account for coefficient estimation

VEC Residual Heteroskedasticity Tests (Levels and Squares)

Date: 01/08/24 Time: 22:34

Sample: 1982 2022

Included observations: 39

Joint test:

Chi-sq	df	Prob.
69.44530	48	0.0231

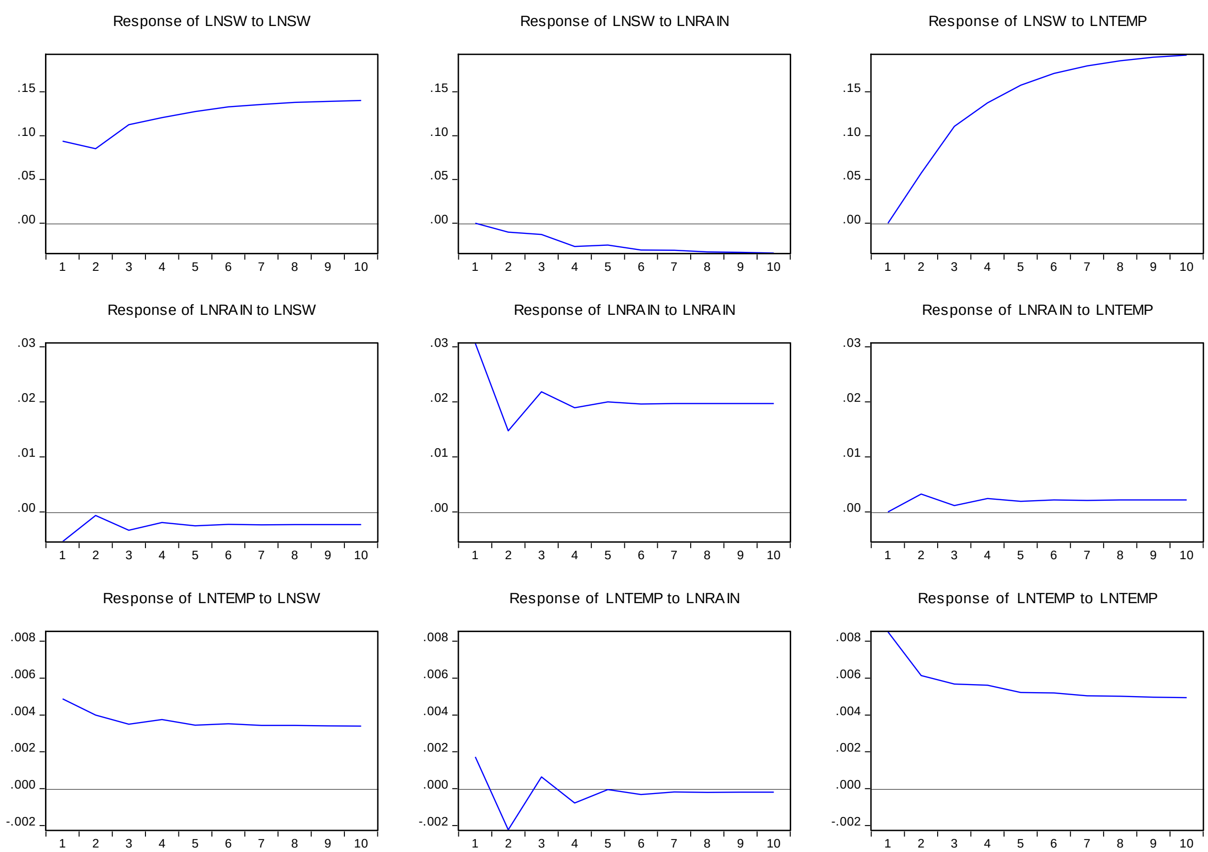
Roots of Characteristic Polynomial
Endogenous variables: LNSW LNRAIN LNTEMP
Exogenous variables:
Lag specification: 1 1
Date: 01/08/24 Time: 22:35

Root	Modulus
1.000000	1.000000
1.000000	1.000000
0.666813	0.666813
-0.406561 - 0.125232i	0.425412
-0.406561 + 0.125232i	0.425412
-0.153976	0.153976

VEC specification imposes 2 unit root(s).

https://dx.doi.org/10.4314/swj.v19i1.11

Response to Cholesky One S.D. (d.f. adjusted) Innovations



Variance Decomposition of LNSW:

Period	S.E.	LNSW	LNRAIN	LNTEMP
1	0.093742	100.0000	0.000000	0.000000
2	0.139404	82.63837	0.530255	16.83137
3	0.210923	64.51990	0.595671	34.88443
4	0.280371	55.00699	1.219556	43.77345
5	0.346904	49.45579	1.312316	49.23190
6	0.410128	45.87663	1.495310	52.62806
7	0.468819	43.47279	1.577405	54.94981
8	0.523793	41.76145	1.653400	56.58515
9	0.575101	40.50209	1.704949	57.79296
10	0.623265	39.54484	1.746274	58.70889

Variance Decomposition of LNRAIN:

Period	S.E.	LNSW	LNRAIN	LNTEMP
1	0.031084	2.959664	97.04034	0.000000
2	0.034558	2.427577	96.68359	0.888836
3	0.041038	2.375036	96.91310	0.711864
4	0.045300	2.129791	96.99685	0.873359
5	0.049614	2.033797	97.08771	0.878495
6	0.053453	1.930536	97.14341	0.926056
7	0.057061	1.862700	97.18572	0.951582
8	0.060452	1.805249	97.21750	0.977247
9	0.063659	1.759790	97.24221	0.998005
10	0.066715	1.721991	97.26220	1.015811

Variance Decomposition of LNTEMP:

Period	S.E.	LNSW	LNRAIN	LNTEMP
1	0.009957	24.02524	3.001938	72.97282
2	0.012557	25.19389	5.071880	69.73423
3	0.014235	25.64505	4.146471	70.20848
4	0.015774	26.54458	3.621875	69.83354
5	0.016969	27.05677	3.130609	69.81262
6	0.018093	27.58197	2.783769	69.63426
7	0.019095	27.98688	2.508530	69.50459
8	0.020038	28.34665	2.288878	69.36447
9	0.020922	28.65191	2.107688	69.24040
10	0.021764	28.91841	1.955071	69.12652

Cholesky Ordering: LNSW LNRAIN LNTEMP

Estimation Proc:
===============================
EC(C,1) 1 1 LNSW LNRAIN LNTEMP

VAR Model:
===============================
D(LNSW) = A(1,1)*(B(1,1)*LNSW(-1) + B(1,2)*LNRAIN(-1) + B(1,3)*LNTEMP(-1) + B(1,4)) + C(1,1)*D(LNSW(-1)) + C(1,2)*D(LNRAIN(-1)) + C(1,3)*D(LNTEMP(-1)) + C(1,4)

D(LNRAIN) = A(2,1)*(B(1,1)*LNSW(-1) + B(1,2)*LNRAIN(-1) + B(1,3)*LNTEMP(-1) + B(1,4)) + C(2,1)*D(LNSW(-1)) + C(2,2)*D(LNRAIN(-1)) + C(2,3)*D(LNTEMP(-1)) + C(2,4)

D(LNTEMP) = A(3,1)*(B(1,1)*LNSW(-1) + B(1,2)*LNRAIN(-1) + B(1,3)*LNTEMP(-1) + B(1,4)) + C(3,1)*D(LNSW(-1)) + C(3,2)*D(LNRAIN(-1)) + C(3,3)*D(LNTEMP(-1)) + C(3,4)

VAR Model - Substituted Coefficients:
===============================
D(LNSW) = - 0.28409292077*(LNSW(-1) + 1.40315591491*LNRAIN(-1) - 41.0740504526*LNTEMP(-1) + 104.880715984) - 0.196814108641*D(LNSW(-1)) - 0.311720218596*D(LNRAIN(-1)) - 4.94481721369*D(LNTEMP(-1)) + 0.169702916094

D(LNRAIN) = - 0.00174102943902*(LNSW(-1) + 1.40315591491*LNRAIN(-1) - 41.0740504526*LNTEMP(-1) + 104.880715984) + 0.00131349672028*D(LNSW(-1)) - 0.538043725417*D(LNRAIN(-1)) + 0.311533324417*D(LNTEMP(-1)) + 0.000344556054361

D(LNTEMP) = 0.00187450281426*(LNSW(-1) + 1.40315591491*LNRAIN(-1) - 41.0740504526*LNTEMP(-1) + 104.880715984) - 0.00335959626413*D(LNSW(-1)) - 0.116441398391*D(LNRAIN(-1)) - 0.20189879222*D(LNTEMP(-1)) + 0.000961156858203

System: UNTITLED
Estimation Method: Least Squares
Date: 01/08/24 Time: 22:41
Sample: 1984 2022
Included observations: 39
Total system (balanced) observations 117

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	-0.284093	0.015117	-18.79243	0.0000
C(2)	-0.196814	0.030478	-6.457590	0.0000
C(3)	-0.311720	0.455067	-0.684998	0.4949
C(4)	-4.944817	1.446121	-3.419367	0.0009
C(5)	0.169703	0.015290	11.09923	0.0000
C(6)	-0.001741	0.005013	-0.347318	0.7291
C(7)	0.001313	0.010106	0.129970	0.8968
C(8)	-0.538044	0.150896	-3.565670	0.0006
C(9)	0.311533	0.479519	0.649679	0.5174
C(10)	0.000345	0.005070	0.067961	0.9459
C(11)	0.001875	0.001606	1.167396	0.2458
C(12)	-0.003360	0.003237	-1.037793	0.3018
C(13)	-0.116441	0.048335	-2.409026	0.0178
C(14)	-0.201899	0.153601	-1.314434	0.1916
C(15)	0.000961	0.001624	0.591844	0.5553

Determinant residual covariance 3.95E-10

Equation: D(LNSW) = C(1)*(LNSW(-1) + 1.40315591491*LNRAIN(-1) - 41.0740504526*LNTEMP(-1) + 104.880715984) + C(2)*D(LNSW(-1)) + C(3)*D(LNRAIN(-1)) + C(4)*D(LNTEMP(-1)) + C(5)
Observations: 39

R-squared	0.928377	Mean dependent var	0.148587
Adjusted R-squared	0.919951	S.D. dependent var	0.331326
S.E. of regression	0.093742	Sum squared resid	0.298777
Durbin-Watson stat	1.158603		

Equation: D(LNRAIN) = C(6)*(LNSW(-1) + 1.40315591491*LNRAIN(-1) - 41.0740504526*LNTEMP(-1) + 104.880715984) + C(7)*D(LNSW(-1)) + C(8)*D(LNRAIN(-1)) + C(9)*D(LNTEMP(-1)) + C(10)
Observations: 39

R-squared	0.273270	Mean dependent var	0.000430
Adjusted R-squared	0.187773	S.D. dependent var	0.034490
S.E. of regression	0.031084	Sum squared resid	0.032851
Durbin-Watson stat	2.175168		

Equation: D(LNTEMP) = C(11)*(LNSW(-1) + 1.40315591491*LNRAIN(-1) - 41.0740504526*LNTEMP(-1) + 104.880715984) + C(12)*D(LNSW(-1)) + C(13)*D(LNRAIN(-1)) + C(14)*D(LNTEMP(-1)) + C(15)
Observations: 39

R-squared	0.279183	Mean dependent var	0.000478
Adjusted R-squared	0.194380	S.D. dependent var	0.011093
S.E. of regression	0.009957	Sum squared resid	0.003371
Durbin-Watson stat	2.362213		